U.P.B. Sci. Bull., Series C, Vol. 71, Iss. 1, 2009 ISSN 1454-234x

FAST METHODS FOR IDENTIFICATION OF VIBRATION DEFECTS

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Diagnoza de defecte este un domeniu care a atins maturitatea în ultimii 10 ani. Succesul monitorizării unui sistem în funcţiune, în vederea detectării de comportamente anormale, depinde într-o măsură covîrşitoare de semnalele capabile să codifice informaţia despre aceste defecte. Un astfel de semnal este, de exemplu, vibraţia emisă de sistemele mecanice. Există mai multe tehnici de diagnoză a sistemelor mecanice plecînd de la vibraţii. In acest articol, discuţia este concentrată numai asupra cîtorva tehnici rapide şi uşor de implementat. Printre ele, cea bazată pe analiza de anvelopă spectrală a stîrnit un mare interes în industrie.

Fault diagnosis is a domain that has reached its maturity within the last decade. The success of monitoring aiming to detect flaws during the functioning of some system tremendously depends on the signals which are encoding the information about possible defects. Such a signal is, for example, the vibration produced by mechanical systems. Several techniques have been devised in order to detect defects starting from vibrations. The paper focuses only on fast and easy to implement such techniques, among of which the one based on spectral envelope analysis is of the greatest interest in industry.

Keywords: time domain synchronous averaging, spectral envelope analysis.

1. Introduction

Acquiring vibrations in order to detect flaws of mechanical systems in operation is not a new idea. Methods of mechanical *fault detection and diagnosis* (fdd) have been devised even at the early stages of machinery history. Although the methods were rather empirical and required a great deal of experience from the human operator supervising the system, the defects could be detected in time. Some of such methods are described in [1] and [2]. Some other methods are targeting the automation of fault diagnosis, starting from the spectral

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representation of vibration and a set of associated statistical parameters, such as: the *root mean square* (RMS) or the *peak value*.

For example, a very interesting approach based on statistics and pattern recognition has been introduced in [3]. This is in fact an attempt of human reasoning automating, which resulted in a quite efficient and simple fdd algorithm, though with unavoidable limitations. A different approach is introduced in [4], where one assumes the largely accepted idea that *human reasoning is also fuzzy*. It follows that solutions to a problem could be issued even from unclear, vague or ambiguous information, i.e. from information, which is strongly affected by uncertainty. Usually, the operator selects the most plausible diagnostic, according to the available data. Therefore, the operator's experience is crucial for diagnosis accuracy. Unfortunately, the operator has to cope not only with external perturbations corrupting the data, but also with his/her own subjectivism. In order to increase objectivity, the operator relies on simple statistical assessments. The reasoning hidden behind data analysis could thus be automated by performing a combination between *spectral statistics* and *fuzzy clustering* (in entropy sense [3]). In this way, both subjectivism and perturbations influence decrease.

However, the most efficient methods in early detection of defects are using *Signal Processing* (SP) techniques [6]. Differently from many typical SP applications, where the noise attenuation is a fundamental requirement, when using vibrations for fdd, the noise is the most concerned part in the analysis. This is due to the fact that not the natural oscillations of machinery could encode the defective behavior, but the noise corrupting them. Moreover, the applications revealed that the *signal-to-noise ratio* (SNR) is extremely small for vibrations encoding information about defects. Therefore, the models of vibration used in fdd are actually models of their noisy parts, encoding information about defect types and severity [1].

The simple structure and large integration within mechanical systems made bearings extremely interesting for fdd in automatic manner [7]. The various bearings defects (as described in [8], [7] or [2]) are mainly encoded by the medium or high sub-bands of vibration spectrum [9]. The effect is due to the specific micro-shocks of defects, which are forcing the sensor to reach the resonance state [1]. Unfortunately, the defect shocks are mixed in an unknown manner with other parasite signals coming from the environment or produced by interferences. Therefore, the detection techniques should be able both to denoise the spectrum and to focus on the sub-bands where the defect seems to be encoded.

One of the most popular method to extract information about defects in bearings (and geared coupling) is the (*Spectral) Envelope Analysis* (EA). This method is described and employed in a case study within the last two sections (3 and 4) of this article. The next section is concerned with a method to perform smoothing of vibrations and spectra, by averaging. (Smooth spectra yield easier detection of faults.) The article completes with a conclusion and a references list.

2. Time domain averaging methods

The single point defect model described in [1] could also be employed to perform fdd of bearings. The method yielding isolation of vibration components that could emphasize the defects (and, eventually, their severity) is based on a technique referred to as *Time Domain Synchronous Averaging* (TDSA) (introduced in [10]). From SP point of view, this technique is quite simple and founded on the concept of *comb filter*: a filter that let only some isolated frequencies pass and cuts all the remaining ones [6]. The main idea of TDSA technique is the following: averaging the signal by using its frames is equivalent to filtering the signal by a comb filter. More specifically, let the averaged signal be computed from frames of vibration signal y, like below:

$$a_v(t) = \frac{1}{N}\sum_{n=0}^{N-1} y(t+nT)\,, \quad \forall\, t \in \mathbb{R} \tag{1}$$

where $N \geq 2$ is the number of averaging frames and $T > 0$ is the time shift step between frames. Then, the averaging operation (1) is equivalent to:

$$a_v(t) = (c * y)(t)\,, \quad \forall\, t \in \mathbb{R} \tag{2}$$

where c is the impulse response of a comb filter, i.e. the average of a finite set of unit impulses:

$$c(t) = \frac{1}{N}\sum_{n=0}^{N-1} \delta_0(t+nT)\,, \quad \forall\, t \in \mathbb{R}\,. \tag{3}$$

Also, in equation (2), c plays the role of *synchronization signal* for vibration.

The *Fourier Transform* (FT) of comb filter (3) is then:

$$C(\Omega) = \frac{1}{N} \mathrm{e}^{j(N-1)T\Omega/2} \frac{\sin\left(NT\Omega/2\right)}{\sin\left(T\Omega/2\right)}\,, \quad \forall\, \Omega \in \mathbb{R}\,. \tag{4}$$

Its spectrum looks like in Fig. 1. The bigger the number of averaging frames (N), the sharper the main lobes of comb filter, the smaller the side lobes and, thus, the more accurate the rays selection in FT of y at frequencies $\{k/T\}_{k\in\mathbb{Z}}$.

Recall now the McFadden-Smith single point defect model described in [1] (with the same notations). Then the TDSA technique could be employed to emphasize some components of raw vibration that encode possible defects. This idea was developed in [11]. For example, since the shock pulses signal, denoted by p, is $T_{in} = 1/\nu_{in}$-periodic, by averaging the vibration data with time shift $T_r = 1/\nu_r \neq T_{in}$, the resulting signal is only concerned with loads and transmission path (convolved by sensor impulse response, h):

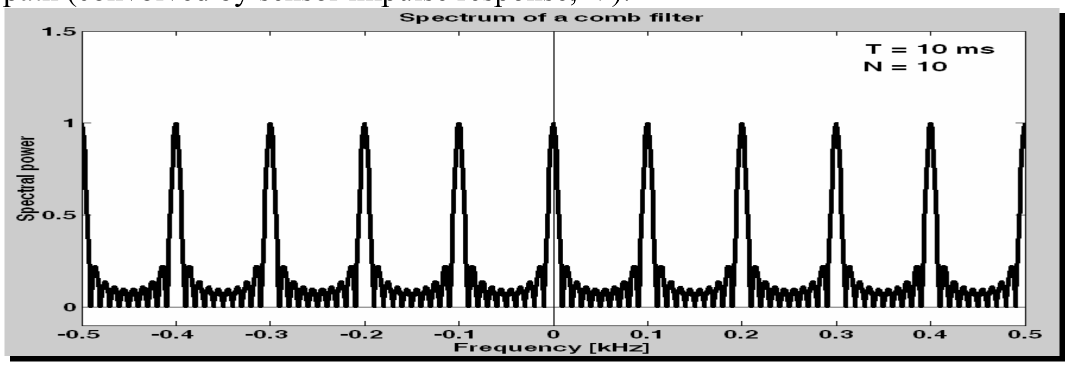

Fig. 1. Spectrum of a comb filter

$$\begin{bmatrix} y_{rot} \equiv h * (q \cdot x) & \text{(in time)} \\ Y_{rot} \equiv H(Q * Y) & \text{(in frequency)} \end{bmatrix}. \tag{5}$$

Thus, the shock pulses have been removed by the comb filter. If the averaging is performed with time shift $n_b / \nu_{in} = 1/(\nu_r - \nu_{cout})$ (i.e. with the period between 2 successive strokes of rolling balls defect), then the resulting signal is p (also convolved by sensor impulse response). This is due to the fact that p constitutes the only vibration component with period $1/\nu_{in} = 1/n_b/(\nu_r - \nu_{cout})$ and thus with period n_b/ν_{in} as well. The resulting average signals are able to reveal single or multiple defects located on the inner race and even their relative spatial positions (angles). The experiments have shown that the average with time shift $n_b/\nu_{in} = 1/(\nu_r - \nu_{cout})$ is better than the other average. That is an expected result, since the shock pulses p are actually produced by inner race defects.

In spite of its remarkable results, a several drawbacks make this method difficult to handle. The number of practical tricks applied in order to decode the information about defects is very large. It follows that, especially in case of multiple defects, the whole rationale behind the method is very difficult to reproduce in an automatic way. Also, the method may not work well for defects located on other constructive parts than the inner race. The severity degree of defect is not necessarily reflected by peak amplitudes within the final signals.

3. Envelope analysis methods

The method that really exploits the sensors resonance in order to extract a clear defect information has been introduced since 1966 [12], improved in 1973 [9] and patented in 1974 [13]. It is referred to as *(Spectral) Envelope Analysis* (EA) (of vibration) and constitutes perhaps the most popular method to extract defect information in bearings and gears.

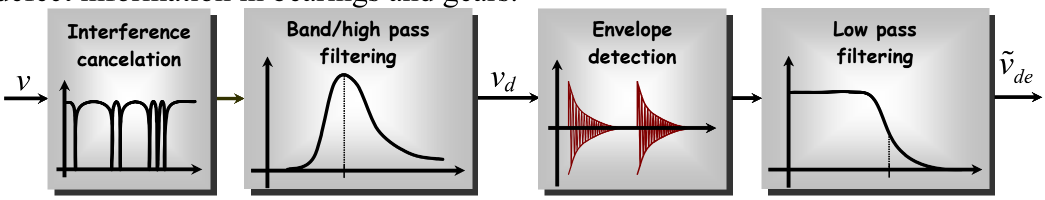

Fig. 2. Main steps of Envelope Analysis Method.

The main steps of EA are summarized in Fig. 2. Sometimes, the interference signals could induce important distortions and should be canceled. This can be realized either directly (if the interference frequencies are a priori known) or automatically. An automatic procedure for interference detection and canceling has been introduced in 1993 [14] and improved in 1996 [15], [16] by D.L. Carter. The most important step of EA is band or high pass filtering, aiming to remove the natural oscillations and to extract only the noisy *high frequency* (HF) part from vibration. Two main problems have to be solved here: the filter shape selection and its localization. Several solutions have been proposed so far (see for example [8], [17], [18], [19], [20], [21]). An efficient solution is introduced in [18] and [19]. The filter shape is suggested in Fig. 2, for a band pass type. There is a central frequency (ν_c) and the low pass attenuation is by far more severe than the high pass attenuation around the center. To induce this effect, the *1/3–octave filter design* is employed, but another design techniques (even more efficient) could be used as well (see [22] or [6]). The name of this technique becomes from the band pass localization around ν_c: 1/3 to the left and 2/3 to the right. In general, the bandwidth is 25% to 50% of ν_c.

The placement of ν_c could be performed either manually (when some more information about vibration is available) or automatically. By automatic procedure, ν_c is placed in the middle of the flattest spectral zone of vibration with lowest energy (where natural oscillation frequencies are seemingly missing). Usually, $\nu_c \in [2,10]\,\text{kHz}$ and, in many papers, $\nu_c \cong 5\,\text{kHz}$. Differently from this recent point of view, in [22], the central frequency is selected around one of the resonance peaks revealed by vibration spectrum (15 or 20 kHz) and its bandwidth is quite sharp (2 kHz). The high pass filters are similarly designed.

Unfortunately, to the best of our knowledge, there are no viable criteria to adaptively design the filters, depending on vibration data. There are only some hints, as pointed for example in [18]: filter the signal such that the spectrum of the noisy (random) component become dominant (i.e. attenuate the basic or induced harmonic components); select the central frequency according to vibration spectrum, at a frequency around of which the fewest large harmonic rays exist; select the filter bandwidth up to 50% (or even 100 %, for high central frequency) of central frequency. Usually, the filters parameters (type, ν_c and bandwidth) are varied until the defect component is the best emphasized next.

One might believe that, by filtering, the information about defects is entirely lost, which is not true, since the sensor saved it within the resonance signal. Actually, this information can be recovered from the envelope of filtered signal v_d. Therefore, a peak follower extracts next the signal v_{de} from v_d. Since v_{de} is basically a *low frequency* (LF) signal, the final low pass filter focuses on the LF zone. Usually the filter cut-off frequency is between 0.8 and 2 kHz. The filtered v_{de} (i.e. $\tilde{v}_{de}$) provides good indications about defect presence, its type and severity. If the machinery is defect free, $\tilde{v}_{de}$ looks practically like a low energy white noise and its spectrum is quasi constant, like in Fig. 3(a). On the contrary, if machinery defects exist, distinctive peaks appear within $\tilde{v}_{de}$ spectrum. The peaks placement encode the defect type, whereas their relative height to the average background spectrum (λ_{de}) encodes the severity degree (see Fig. 3(b)).

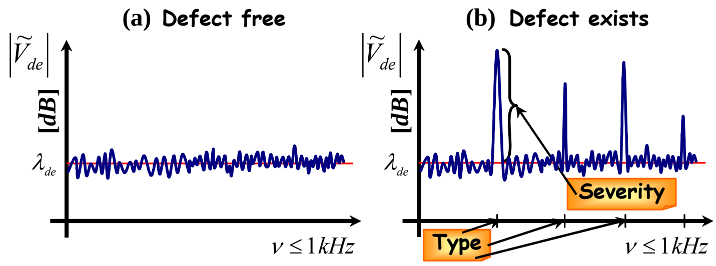

Fig. 3. Envelope vibration spectra.

For example, if peaks are 1% above λ_{de}, de defect is *incipient*. For 5%, the defect evolution reached its *maturity*, whereas for 10% and more, the defect is *severe*. Interestingly, the peaks are located at frequencies strongly related to natural frequencies produced by defective parts of mechanical system (a bearing or a gear). This result has already been devised by using the theoretical McFadden-Smith model. The direct correspondence between peaks location and defect types is described in the end of section (for bearings).

Nowadays, the EA technique is adopted by many manufacturers, especially for its simplicity and low cost implementation. Moreover, a quasi universal defect detector has been constructed and commercialized by VAST Inc. (Russia) in collaboration with VibroTeK Inc. (USA) (www.vibrotek.com): *Diagnostic Rolling Element Analysis Module* (DREAM) [8], [23]. DREAM is incorporated since early 90's inside both American and Russian industries and is practically considered the standard tool in fdd of rolling mechanisms. One of the first defect detectors produced by the companies mentioned above is DC-11 [24], [25], which could be connected to a PC or notebook, like in Fig. 4, to the left.

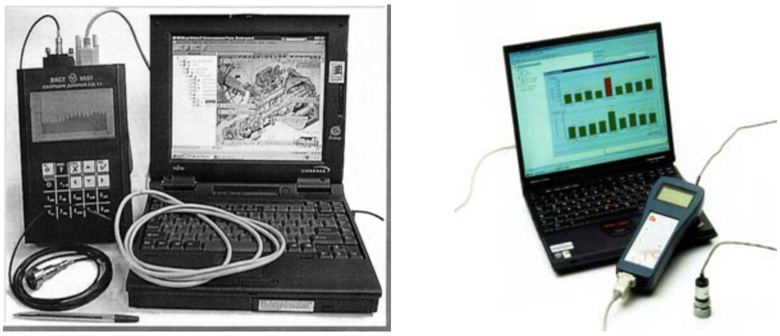

Fig. 4. DC-11 (left) and FAG-2000 (right) defect detectors

Another countries such as United Kingdom, Canada or Denmark also adopted DREAM or DREAM-like techniques for their industries [24]. In Germany, some leading bearing manufacturers integrated the EA within their detectors as well. For example, the modern and light detector in Fig. 4, to the right, is made at German FAG Company (www.fag.de) [26], [27]. (In front of both detectors, sensors (accelerometers) have been pictured.)

Note that EA is not dedicated only to bearings fdd (although bearings constitute its traditional application field). In general, it could be applied wherever is necessary to perform diagnosis of a rotating machinery. For example, gears or geared coupling could also be tested by means of EA [28].

Although widely employed (mainly through DREAM module), EA has some drawbacks. An important one is revealed for multiple machinery defects, when the peaks are extremely mixed. This limitation is probably due to the classical Fourier approach. The frequency content of vibration is not constant, but time varying. (Time-frequency techniques have been considered instead, as described in [29], with very good results.) Another caveat of EA is that the selection of filters aimed to isolate the defect encoding frequency band is quasi-empirically performed, albeit the method is extremely sensitive to these filters. Also, EA is sensitive to envelope construction method (i.e. to peak follower quality). A large number of data acquisition and pre-processing tricks are necessary for defect isolation and recognition. Since EA is not using a mathematical model of vibration, long learning stages are necessary before the diagnosis be accurate. For example, in [18], the authors claimed that, before designing the DREAM module, tests on 1000 machines and more than 100,000 bearings were necessary.

And yet, EA is very useful in early detection of faults, when, usually, only single point defects start to develop. Also, the simple technique to estimate severity degrees with good accuracy by using the envelope spectrum is an extremely practical feature. In most practical cases, this parameter is extremely important for an efficient maintenance of rotating elements. Some applications of EA are described for example in: [30] (fdd for slow rotating bearings), [31] (fdd for transportation applications using vibro-acoustic signals) or [32] (where the lubrication layer plays an important role in fdd).

When integrated in several bearing testers, DREAM is able to detect and identify up to 12 different defect types, as listed next [8]:

1. Revolution around outer (frozen) race: $\nu_d = \nu_r$.
2. Radial tension of bearing: $\nu_d = 2\nu_r$.
3. Slip of race in the mounting seat: $\nu_d \in \{k\nu_r\}_{k\in\mathbb{N}^*}$ (when the spectral power is approximately constant or decays slowly).
4. Wear of inner race: $\nu_d \in \{k\nu_r\}_{k\in\mathbb{N}^*}$ (when the spectral power decreases towards HF).
5. Spalls or cracks on inner race: $\nu_d \in \{k\nu_{in}\}_{k\in\mathbb{N}^*}$.
6. Wear of outer race: $\nu_d = \nu_{out}$.
7. Spalls or cracks on outer race: $\nu_d \in \{k\nu_{out}\}_{k\in\mathbb{N}^*}$.
8. Misalignment of outer race: $\nu_d = 2\nu_{out}$.
9. Spalls, cracks or chops on rolling elements: $\nu_d \in \{k\nu_b\}_{k\in\mathbb{N}^*}$.
10. Wear of rolling elements and/or cage: $\nu_d = \nu_{cout}$ or $\nu_d = \nu_r - \nu_{cout}$.
11. Multiple defects on rolling surfaces (without specifications about location and nature of defects): $\nu_d = \nu_{in} + \nu_{out}$ or $\nu_d = \nu_r + \nu_{out}$ or $\nu_d \in (\nu_r - \nu_{cout})(n_b + 1)$, but $\nu_d \neq \nu_{out} - \nu_r$ and $\nu_d \neq (\nu_r - \nu_{cout})(n_b - 1)$.
12. Lubrication defects: increase of spectral power at all levels.

The list put into correspondence the defect type and the abnormal rays in envelope spectrum (see Fig. 3(b)), located at frequencies ν_d, which are related to natural frequencies. Usually, the outer race is frozen and the inner race is rotating.

The DREAM performances are completed by its statistical behavior. Thus, the probability of identification for defects varies as follows: more than 90% for spalls/cracks/chops on balls or on inner/outer races; more than 80% for wear of balls or outer race and for lubrication defects; more than 70% for misalignment of outer race and wear of multiple surfaces; below 70% for the remaining defect types above (some of them with small probabilities).

The actual stage of fdd for rotating machinery has been analyzed in some papers like [24] or [33], but all of them are emphasizing only EA as the most efficient method. There are however some other promising non conventional methods, as revealed not only by [3] (using statistics and pattern recognition), but also, for example, by [34], [35], [36], [37] or [38] (in general based on fuzzy or neuro-fuzzy approaches).

4. Simulation results

A case study completes the article. Two rolling bearings with identical geometry were tested by means of the platform described in [4]. One of them is defect free (but after several days of running under a light load), whereas the other one has a medium severity chop on the inner race (with estimated severity degree of about 3.5 on the scale of 10 levels). A vibration segment of about 1.3 s (sampled at 25.6 kHz) and its full band spectrum (0-12.8 kHz), in dB, are depicted in Fig. 5 and 6, to the left. To the right, the corresponding LF sub-band of envelope spectrum (at linear scale) is illustrated.

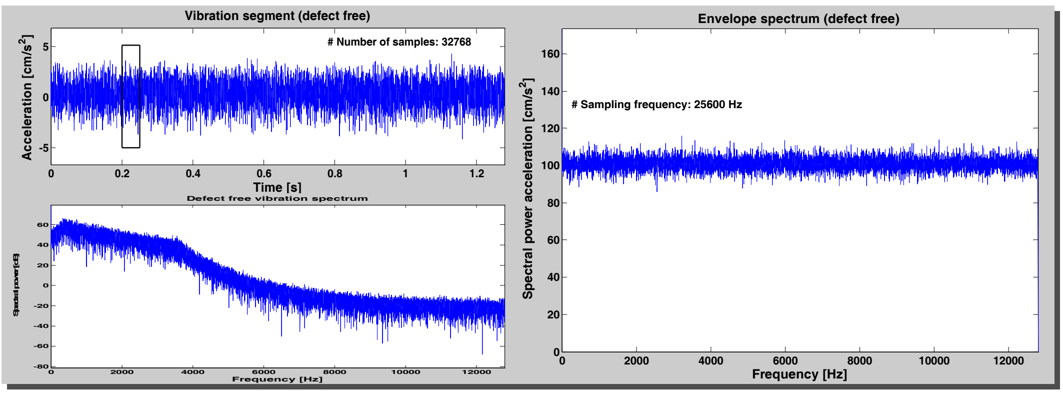

Fig. 10. EA of a defect free bearing

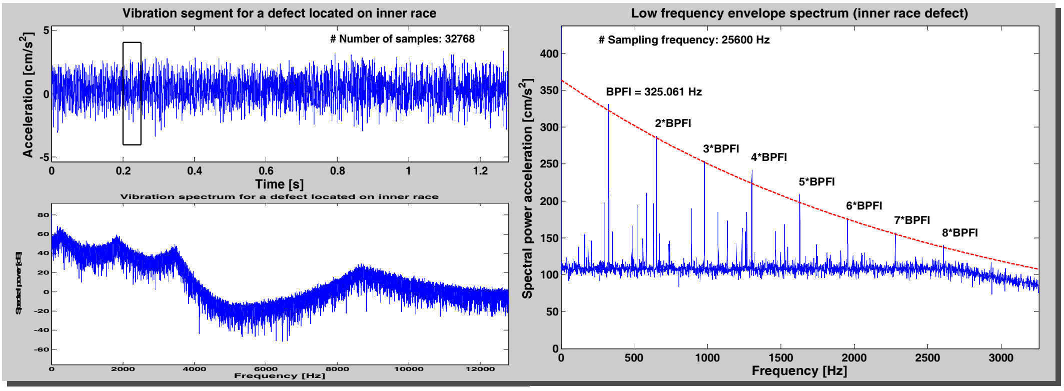

Fig. 11. EA of a bearing with a chop on inner race

In case of defect free bearing (Fig. 5), vibration data are approximately harmonic, with energy concentrated in LF sub-band. The spectrum proves a fast decay towards HF sub-band and the envelope spectrum looks like the white noise spectrum. On the contrary, for the defective bearing (Fig. 6), the vibration data are irregular. The harmonic behavior seems to be sunk into a noisy signal. The spectrum reveals several peaks due to sensor resonance, replicated towards the LF and MF sub-bands. A peak located at about 8 kHz could clearly be distinguished. This behavior is better emphasized by the envelope spectrum, where peaks located at multiples of $\nu_{in} \cong 325\ \text{Hz}$ are exponentially decaying. The first peak is about 3.5 times higher than the average of defect free envelope spectrum, which gives an estimation of defect severity degree.

5. Conclusion

Without any doubt, the research concerning fdd by means of vibrations has advanced beyond the methods described above. However, adoption by big companies from all around the world of modern (and often sophisticated fdd methods) is postponed for future. On the contrary, in spite their limitations, methods like EA reveal that science can become economically attractive by proposing coherent technologies, which are easy to implement.

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